Using SOM neural network to improve land use and cover training samples from satellite image time series

BRAZIL DATA CUBE

AMAZON FUND

INPE

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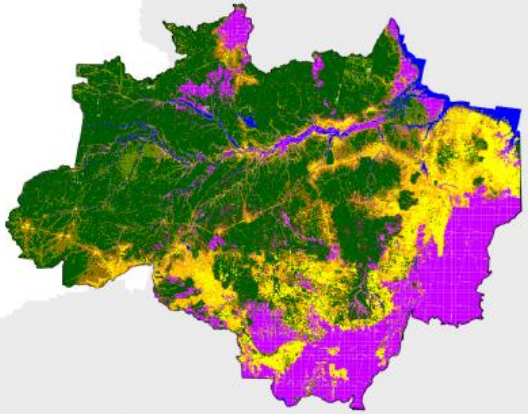
We produce the official land use and cover information in Brazil using Earth Observation Data (EO).

So far, we are using **methods** based on visual interpretation of remote sensing imagery.

PRODES

Deforestation accounting

SINCE 1988

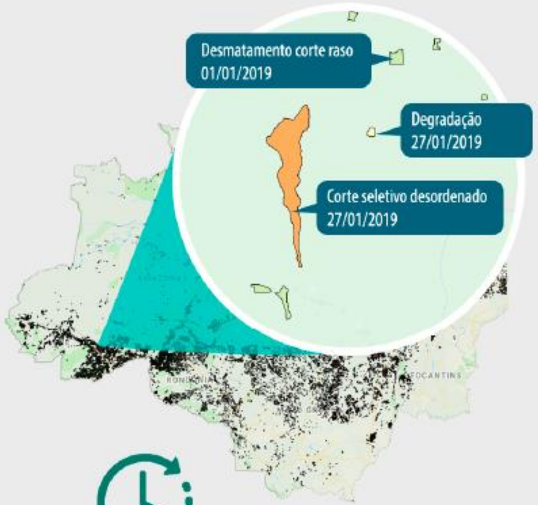


Annual maps

DETER

Deforestation monitoring

SINCE 2004

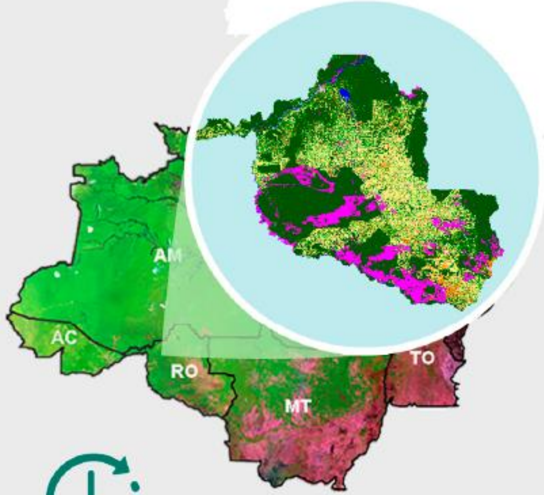


Daily alerts

TERRACLASS

Land use following in deforested areas

SINCE 2004



Biannual maps

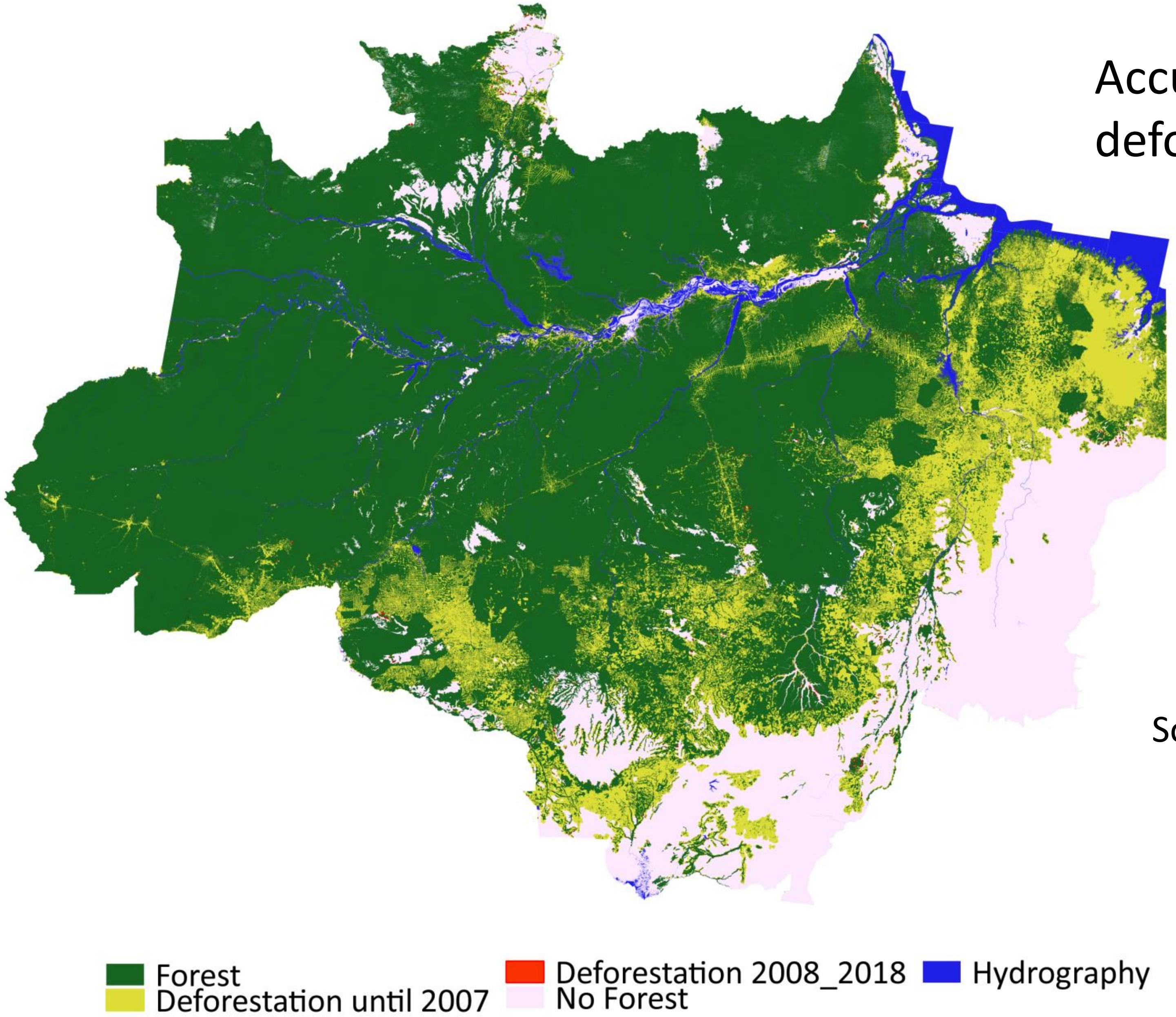
Brazil National Institute for Space Research (INPE)

Projects

e-Sensing: to move from EO visual interpretation to semi automatic classification based on machine learning.

Brazil Data Cube: to produce, process and analyze big Earth observation data sets for land use and cover change detection.

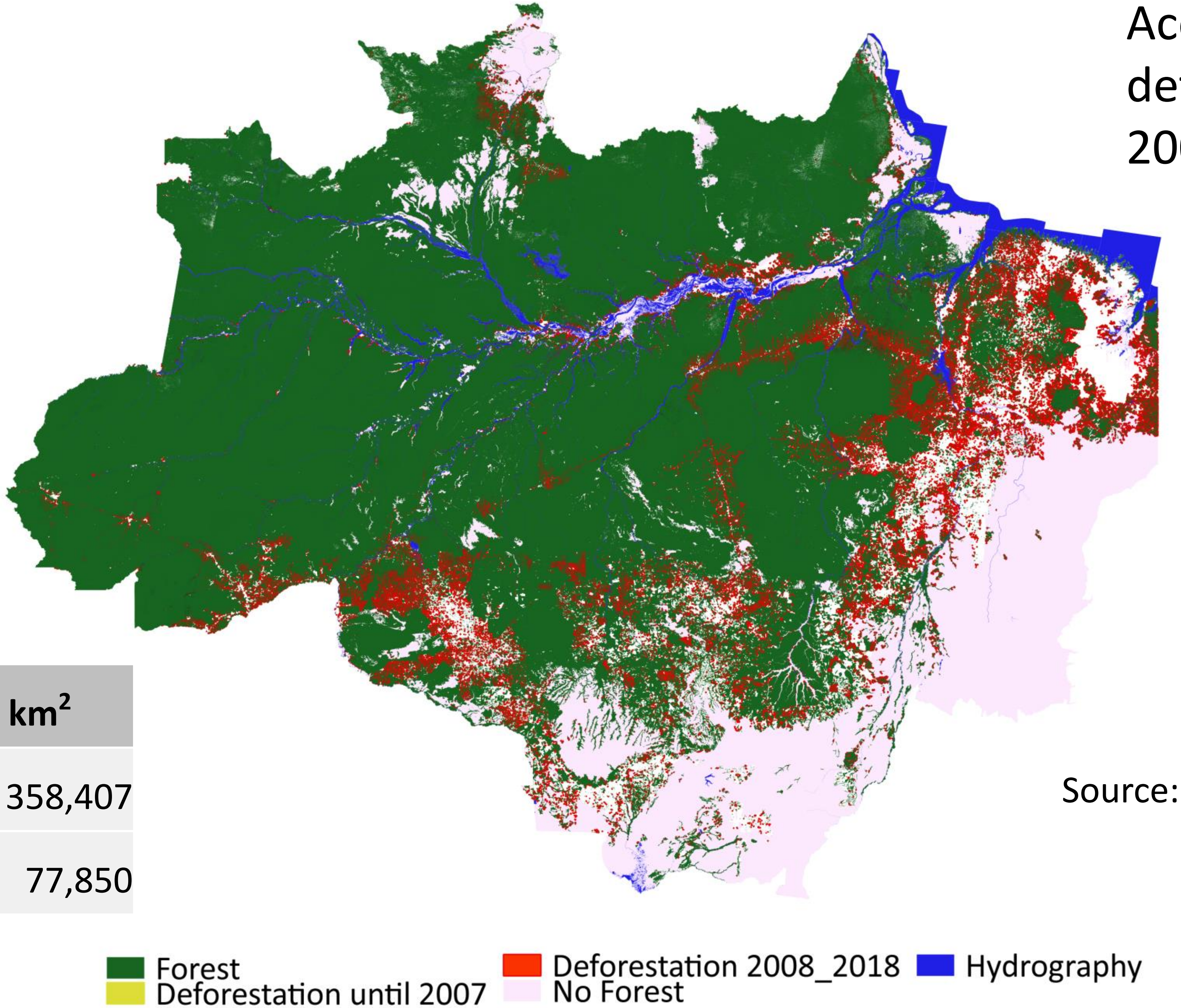
Why should we care about mapping land use?



Accumulated deforestation in 2007

Source: PRODES

Accumulated deforestation from 2008 to 2018

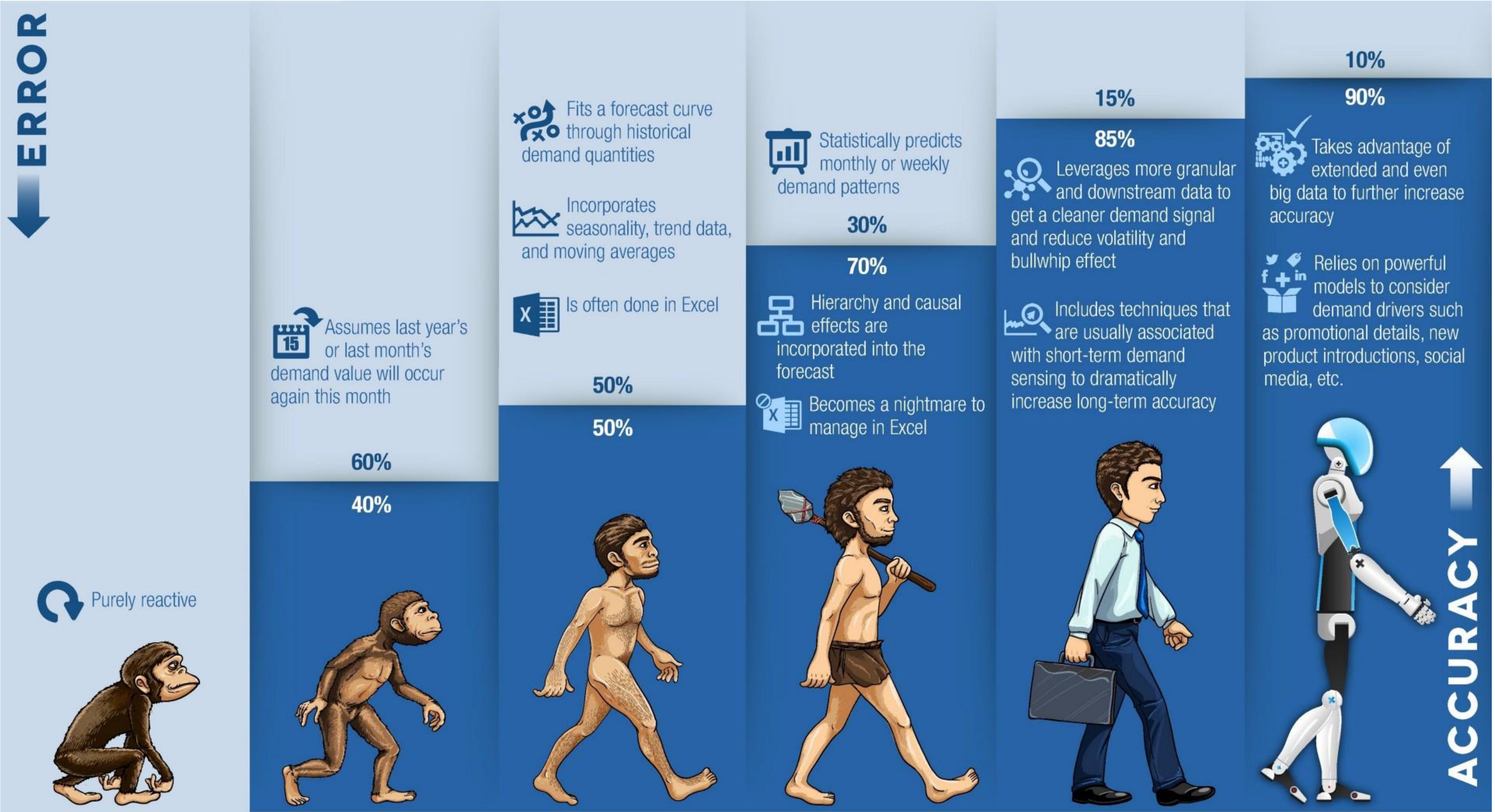


Source: PRODES

Deforestation	km^2
Until 2007	358,407
From 2008 to 2018	77,850

Machine Learning

source: toolsgroup.com



Our analysis as good as our data

by Gary Locke

How do we improve the samples?

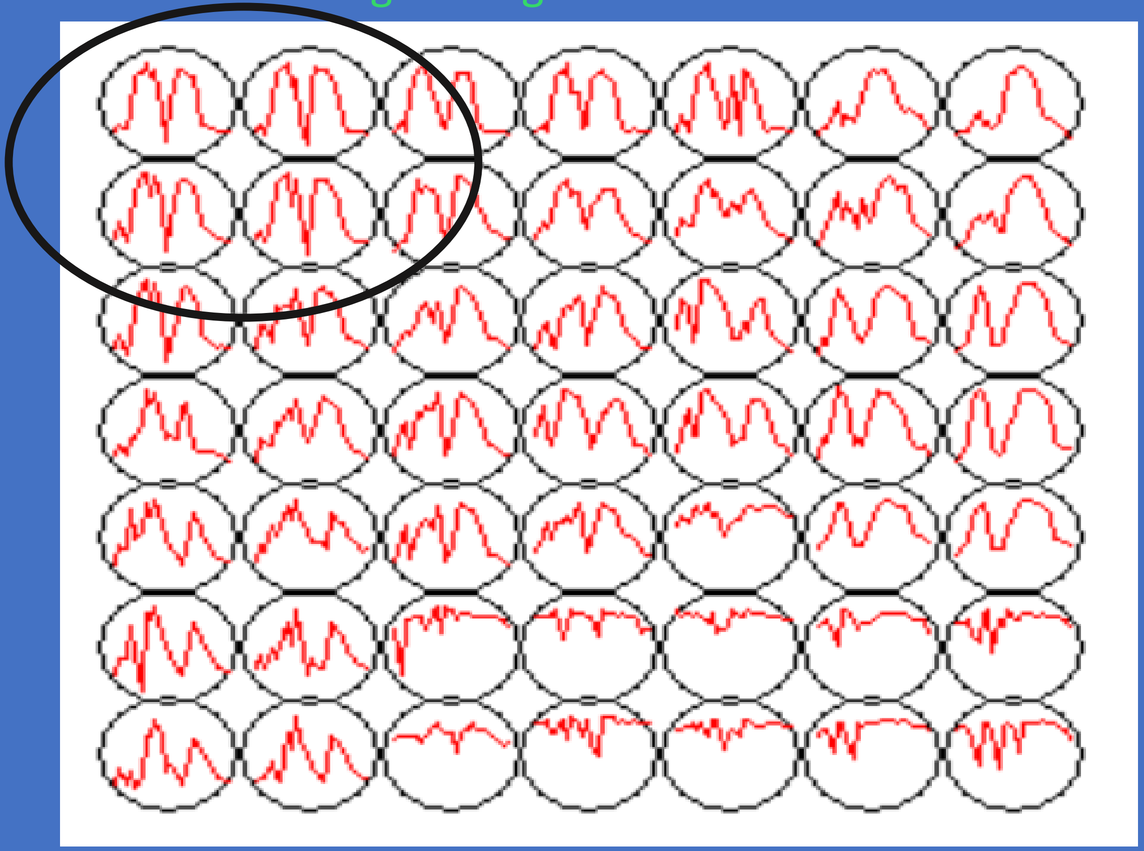
Self-Organizing Maps (**SOM**) neural network method to cluster

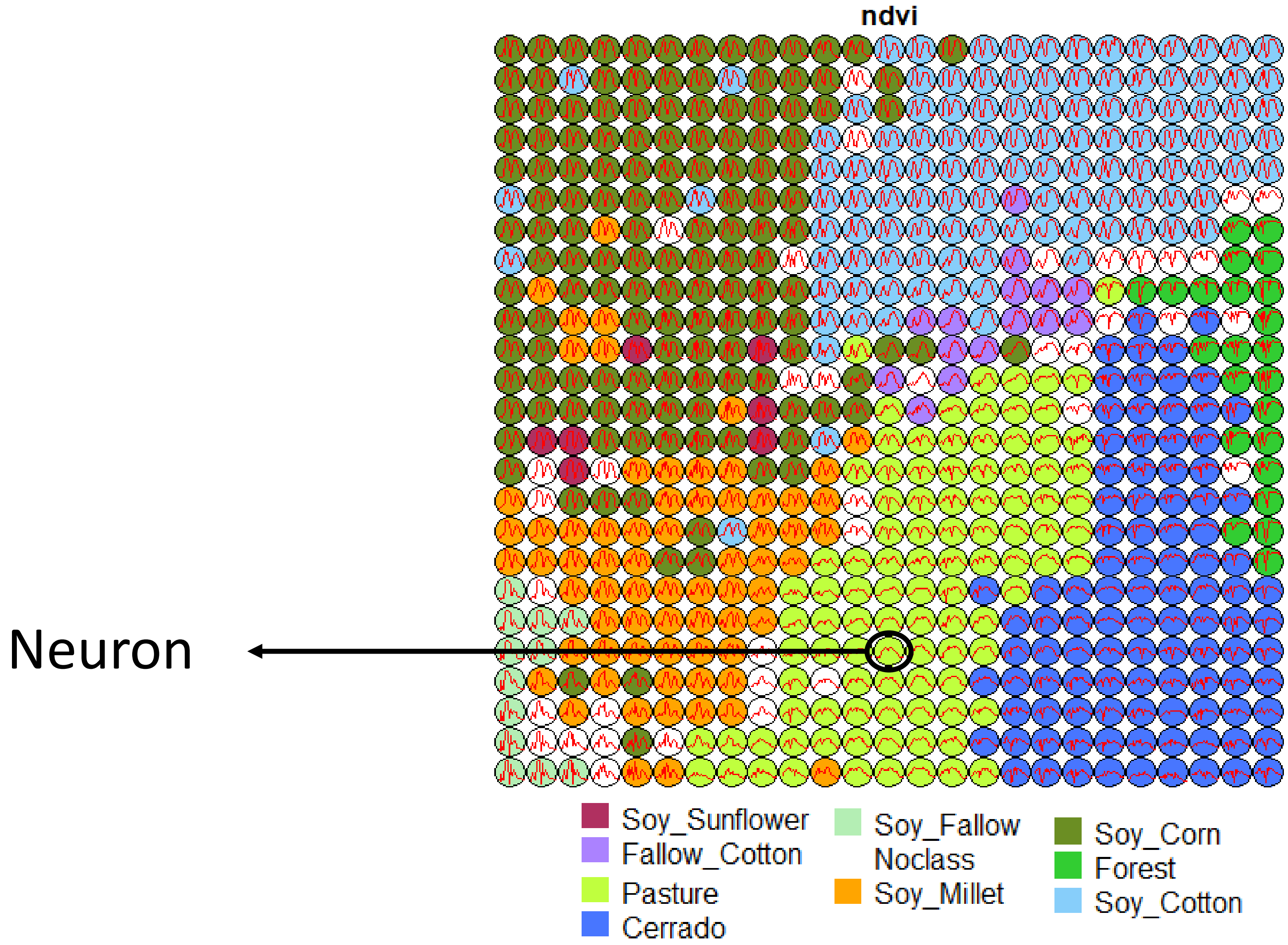
To improve the quality of the training sets for the machine learning classifiers.

To evaluate which spectral bands and vegetation indexes are best suited for splitting among land use-cover classes.

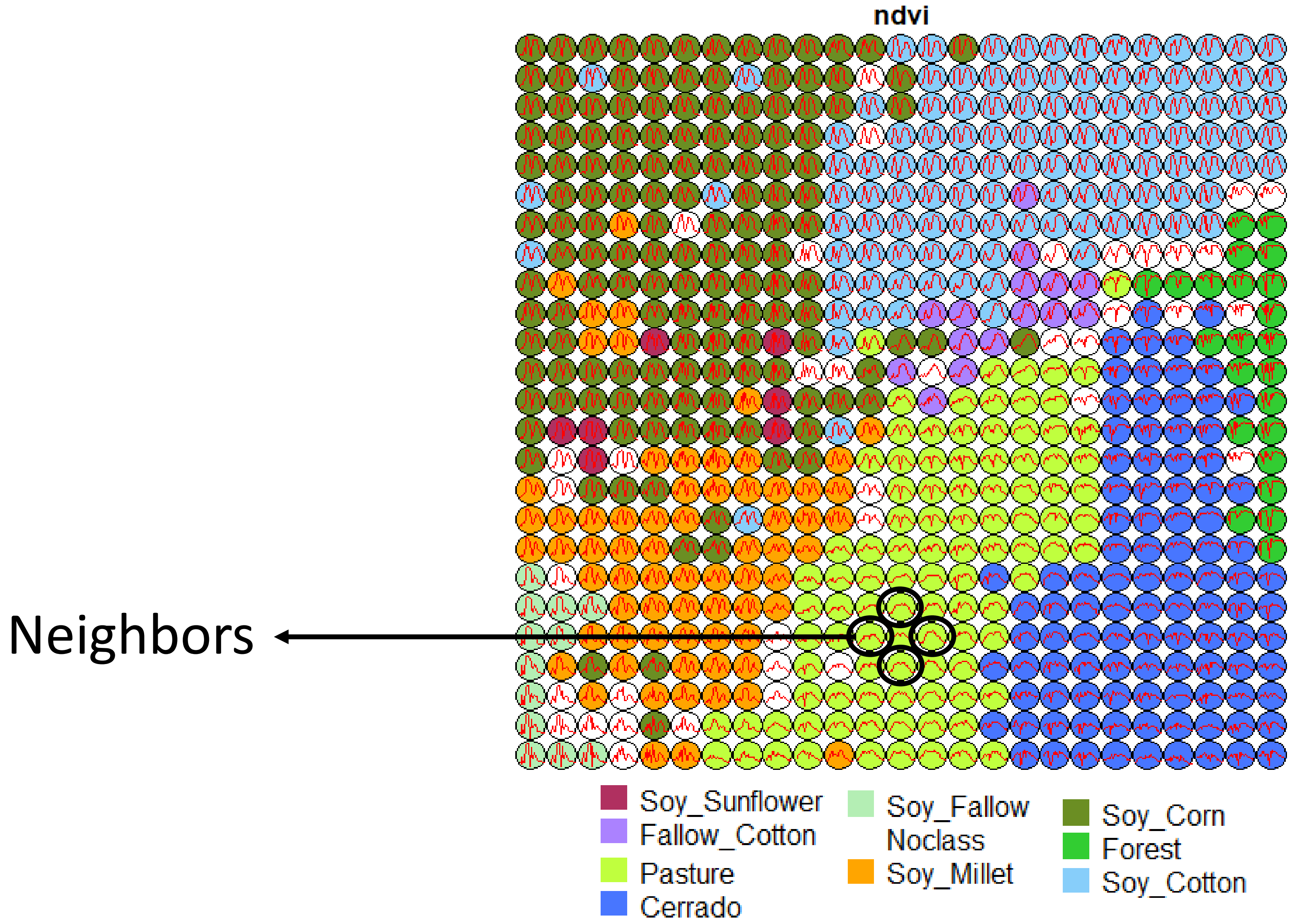
SOM generates spatial clusters of similar patterns.

neighboring neurons are similar!



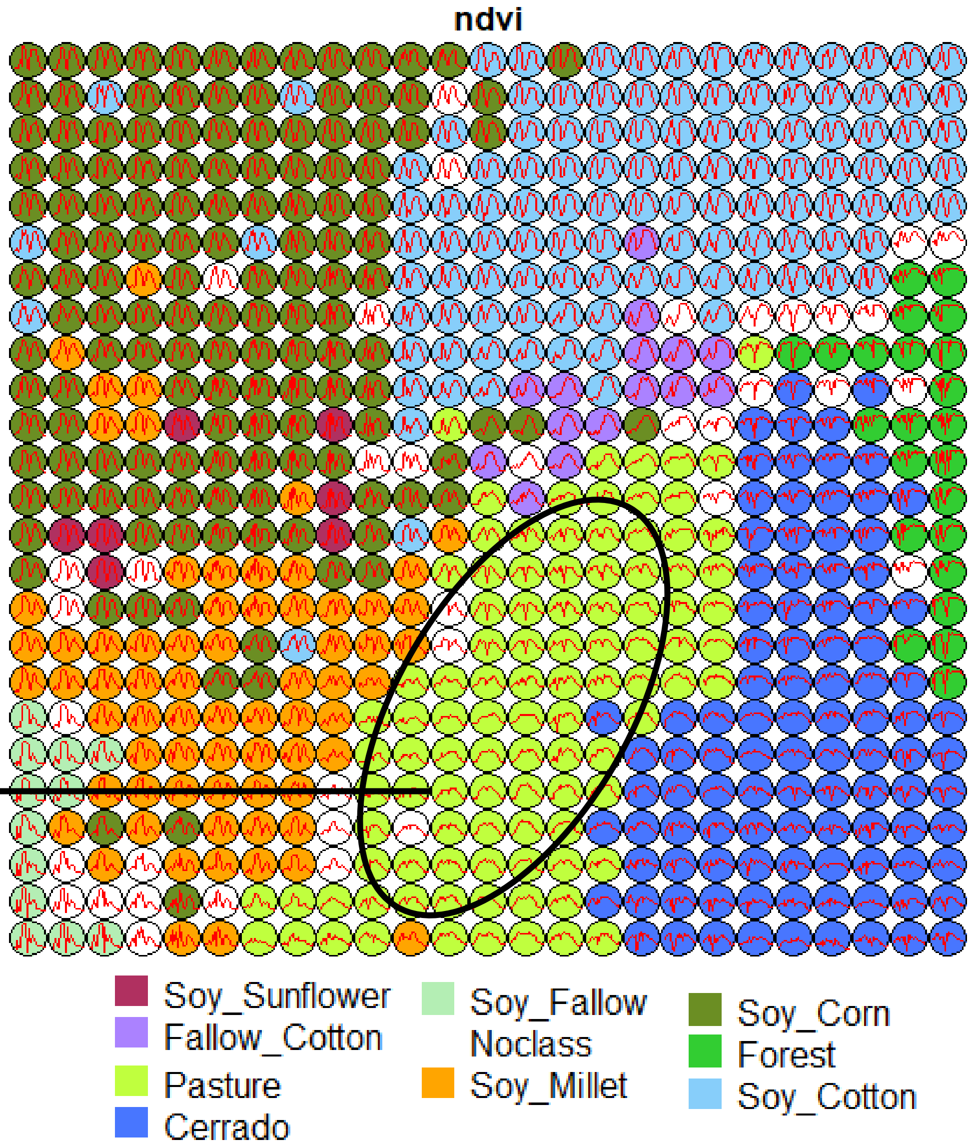


Source: Santos et al. (2019)

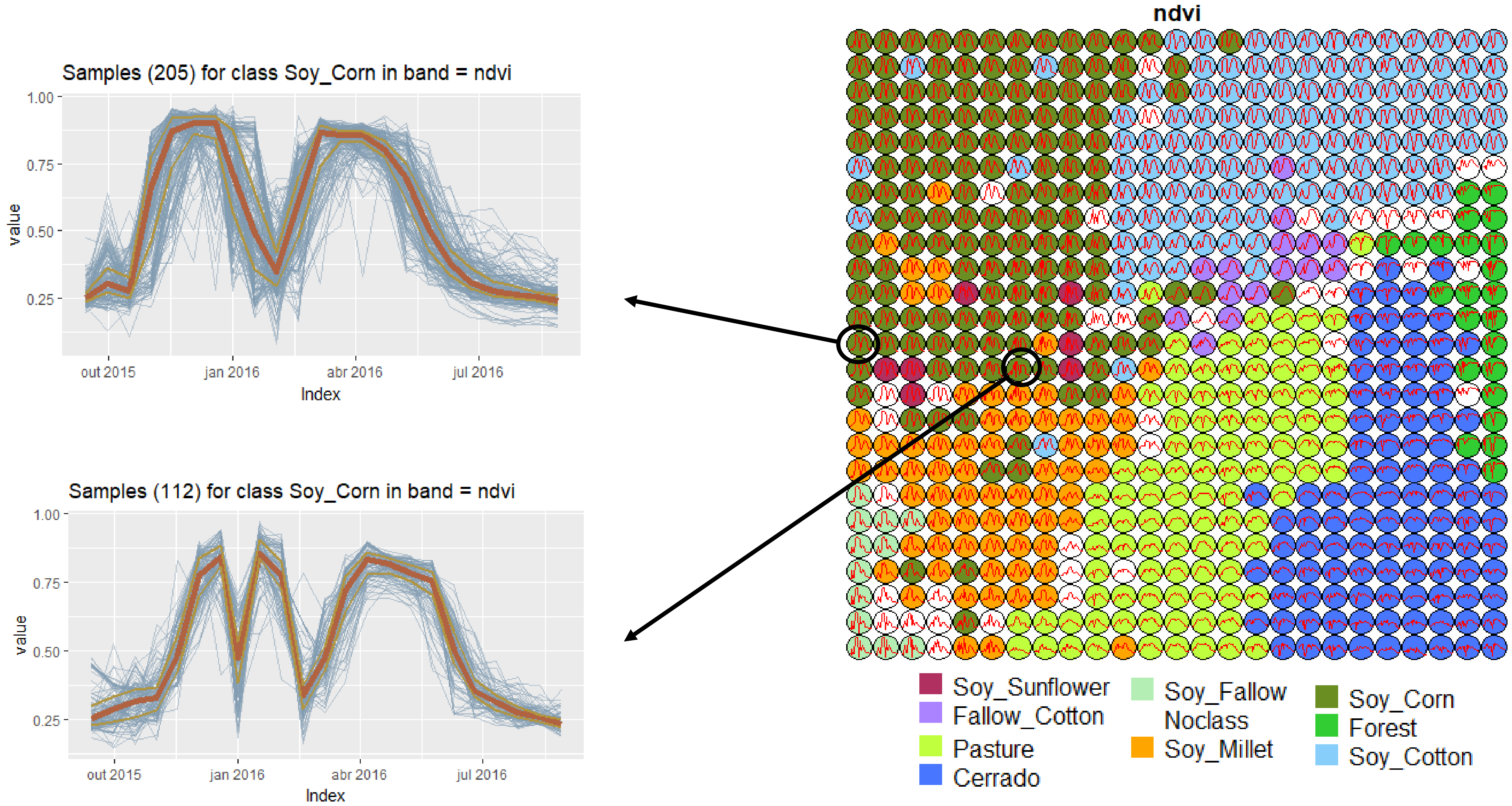


Source: Santos et al. (2019)

Cluster



Source: Santos et al. (2019)

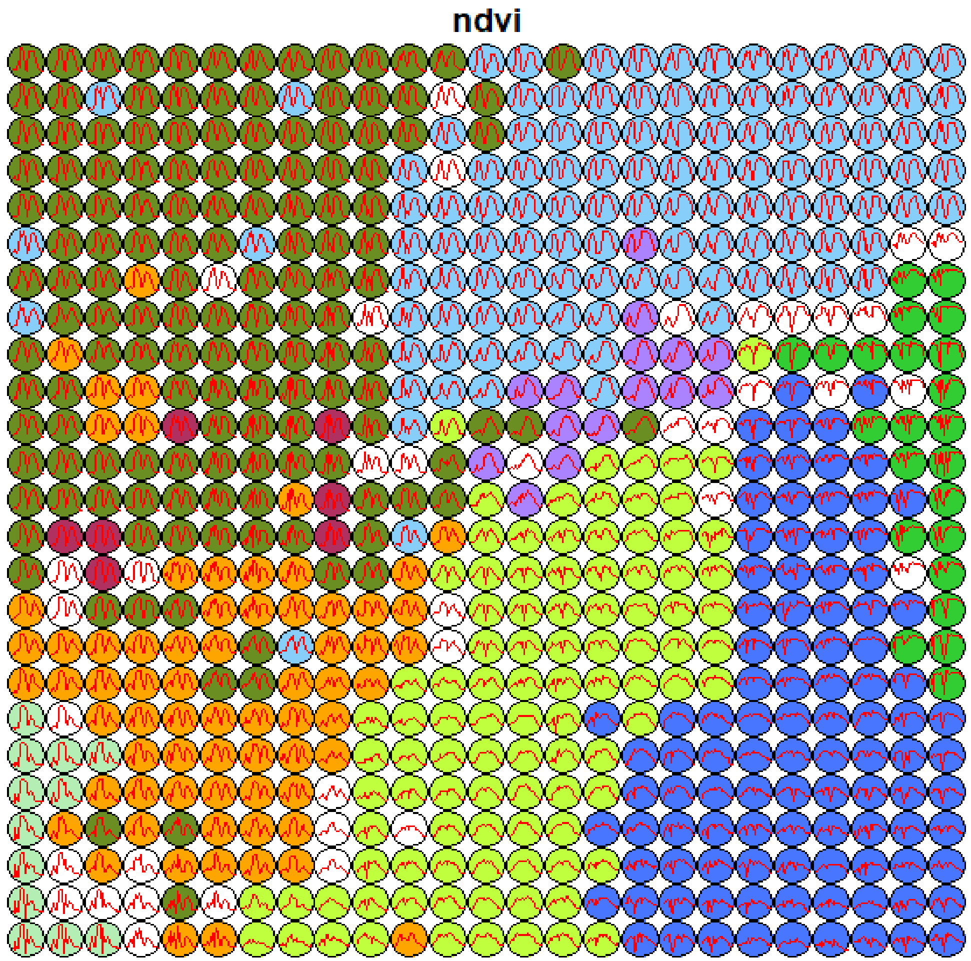


SOM can deal with the variability of vegetation phenology better than other methods.

Source: Santos et al. (2019)

We link each sample to the closest neuron. We minimize the distance iteratively.

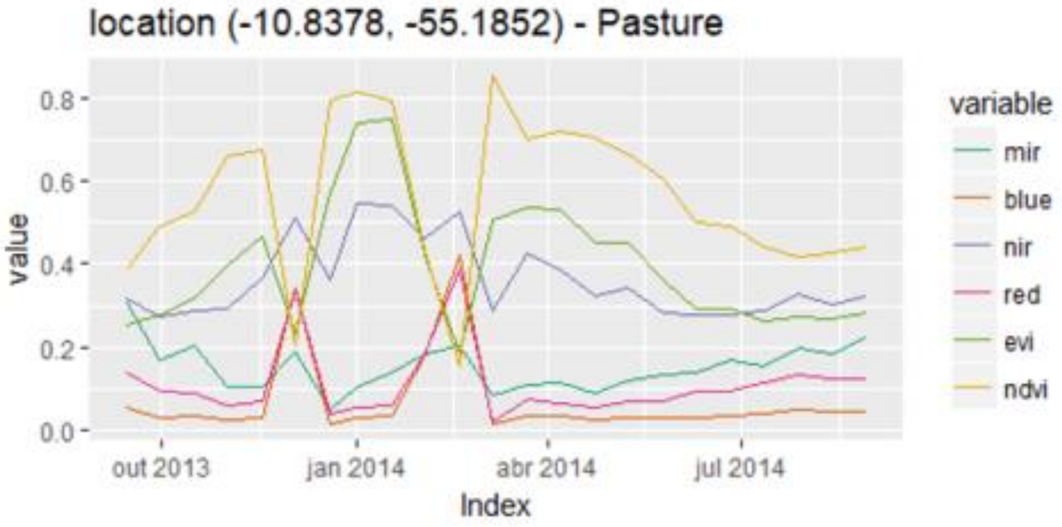
To label a neuron, we choose the most frequent sample label.



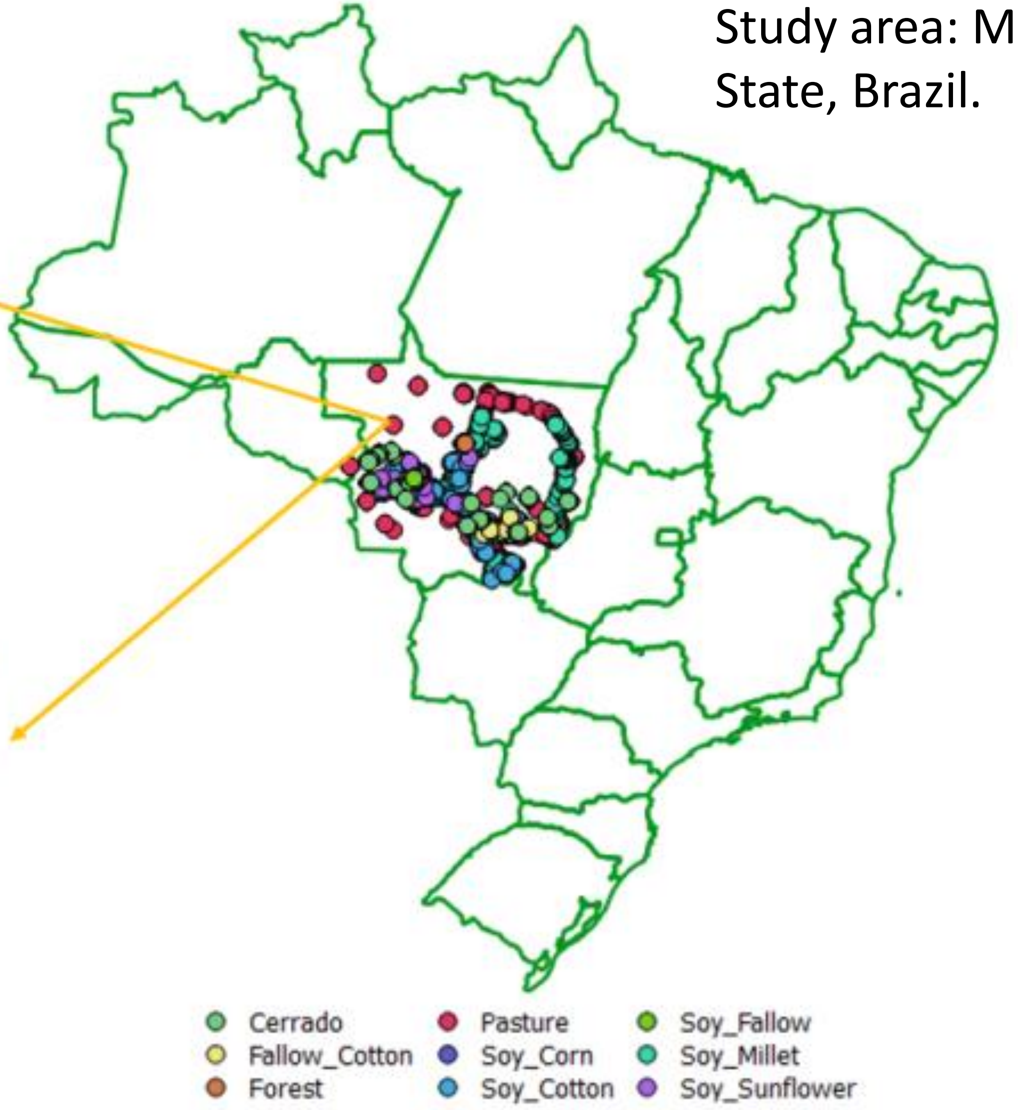
Experiment - Data

2,115 ground sample points (from 2000 to 2013) of nine land use and cover classes.

longitude	latitude	start_date	end_date	label
-55.1852	-10.8378	2013-09-14	2014-08-29	Pasture
-57.7940	-9.7573	2006-09-14	2007-08-29	Pasture
-51.9412	-13.4198	2014-09-14	2015-08-29	Pasture
-55.9643	-10.0621	2005-09-14	2006-08-29	Pasture
-54.5540	-10.3749	2013-09-14	2014-08-29	Pasture

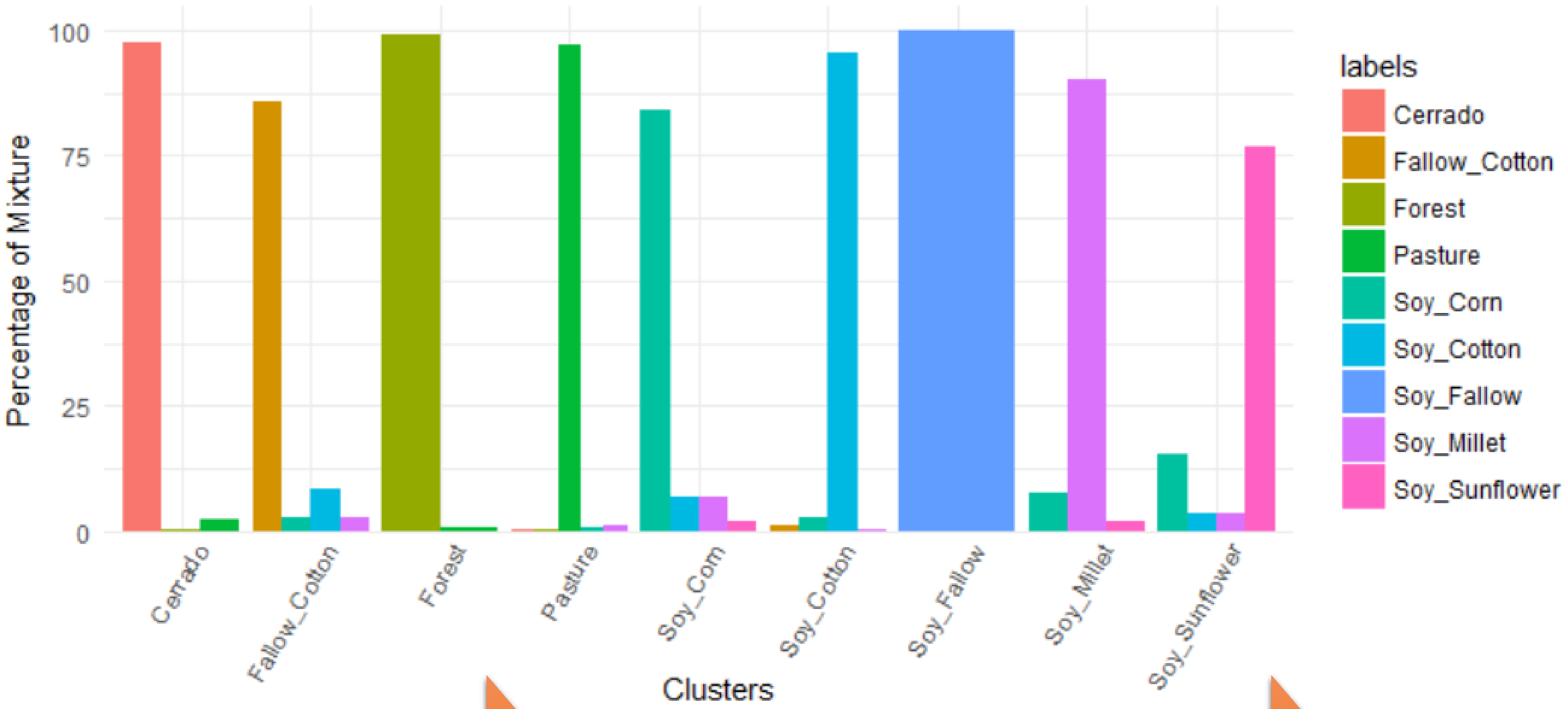


Study area: Mato Grosso State, Brazil.



Source: Camara et al. (2017)

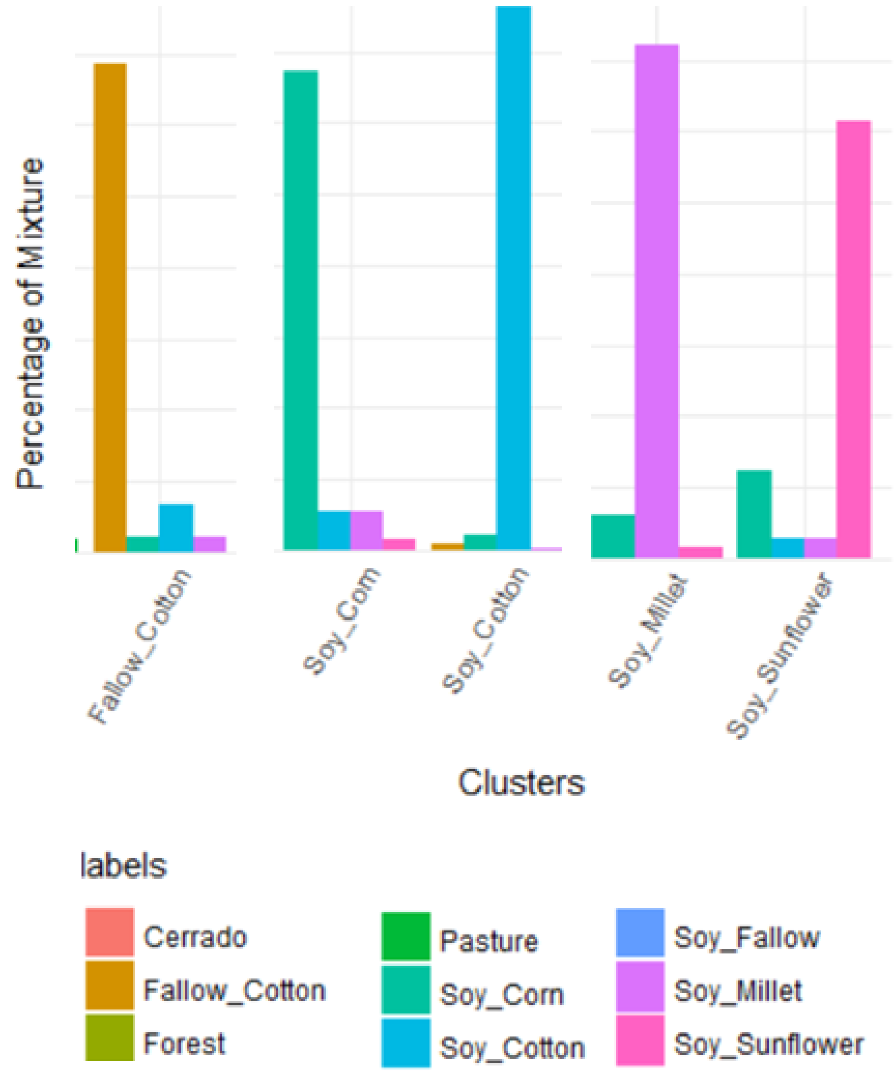
Experiment - Results

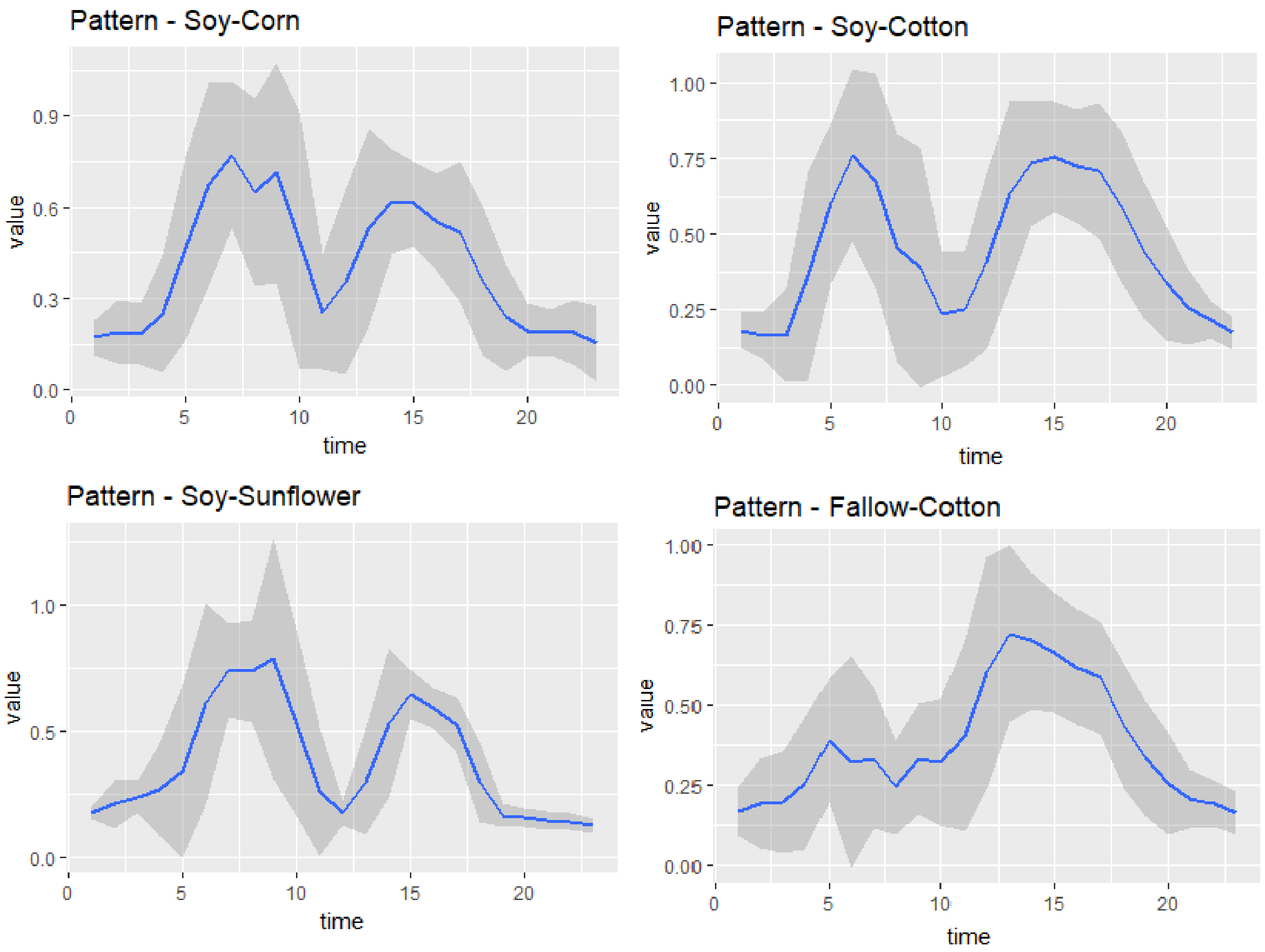


ground samples: 2,115 After SOM 1,892

overall accuracy: 93% After SOM 96%

Experiment - Results

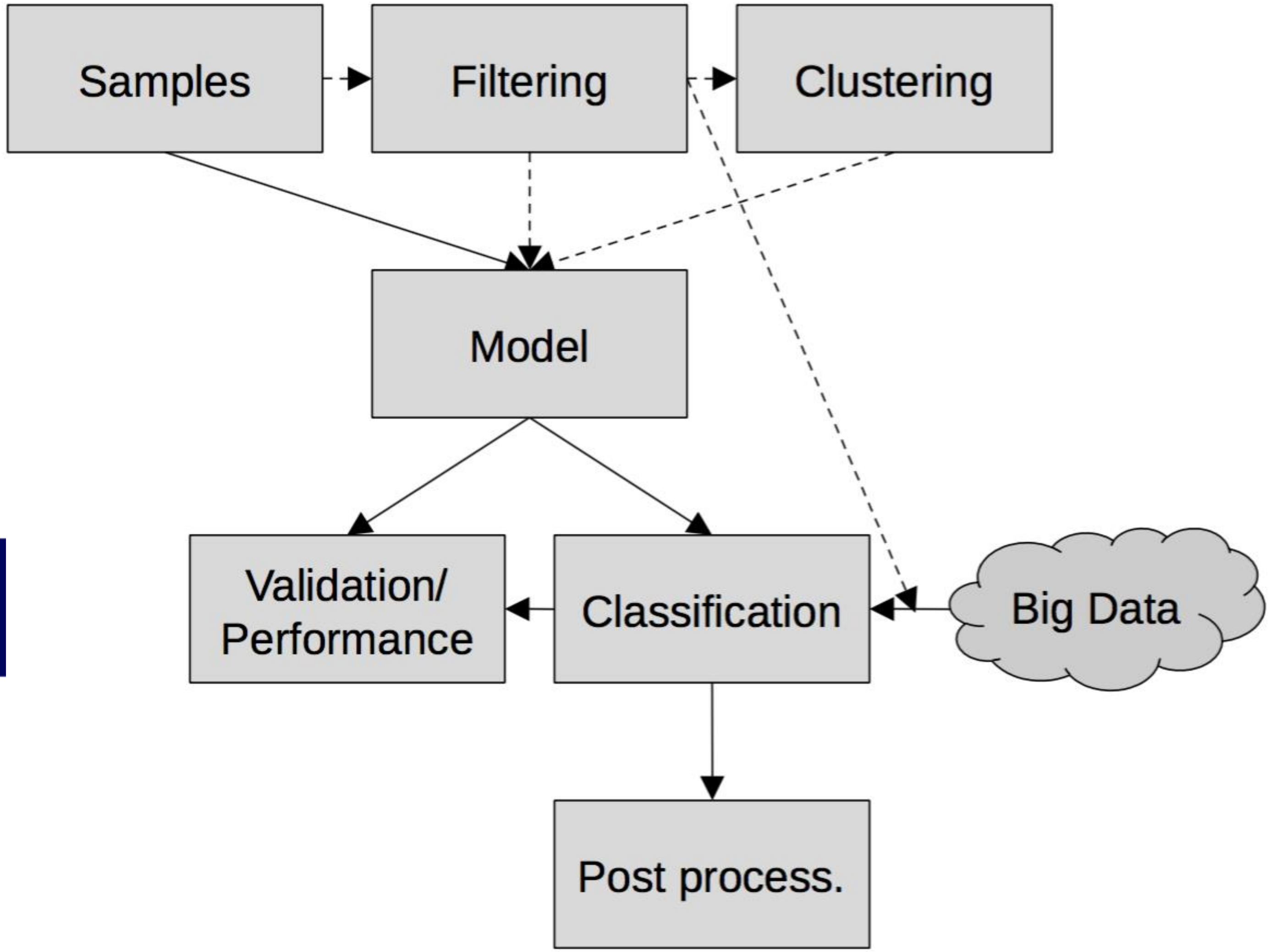




The clusters Soy-Corn and Soy-Sunflower are the most confusing.

sits (Satellite Image Time Series) - R package

github.com/e-sensing/sits



Clutering:

Self-Organizing Maps – SOM (kohonen)

Machine Learning Models:

Support Vector Machine (e1071/LibSVM)

Random Forest
(RandomForest)

Deep Learning (Keras/TensorFlow)

Linear/Quadratic Discriminant Analysis
…

References

Santos et al. (2019) **Self-Organizing Maps in Earth Observation Data Cubes Analysis.**

https://doi.org/10.1007/978-3-030-19642-4_7

Camara et al. (2017) **Land cover change maps for Mato Grosso State in Brazil: 2001-2016**

https://doi.org/10.1594/PANGAEA.881291

Thank you!

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